Mapping tillage practices over a peri-urban region using artificial neural networks applied to combined spot and asar/envisat images

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MAPPING TILLAGE PRACTICES OVER A PERI-URBAN REGION USING ARTIFICIAL NEURAL NETWORKS APPLIED TO COMBINED SPOT AND ASAR/ENVISAT IMAGES

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ABSTRACT

This study aimed at assessing the potential of combining synchronous SPOT4 and ENVISAT/ASAR images for mapping tillage practices of bare agricultural fields over a 220 km²- peri-urban area located in the western suburbs of Paris (France). The approach relied on topsoil roughness measurements combined with information about tillage operations: 28 reference zones demarcated according to soil map information, the visual interpretation of the SPOT4 infrared coloured image and their standard deviation of surface height were related to the backscattering coefficient of the ASAR image (R^2 0.70). They were then used for training/validating neural networks on co-registered 20 m-SPOT/ASAR 6 bands with 15 bootstrapping iterations. The overall mean validation accuracy was 94.9%, while the producer's and user's mean validation accuracies were 91.6-81.5% and 61.8-75.4% for smooth and rough surfaces respectively. The SPOT/ASAR synergy thus enabled to map soil tillage operations with reasonable accuracy.

Index Terms— SPOT/ASAR synergy, tillage practices, bare agricultural soils, mapping, soil roughness

1. INTRODUCTION

Many studies aiming at assessing soil surface characteristics or soil properties for cultivated fields have used either multispectral satellite images (e.g. [1] to [5]) or radar sensors (e.g. [6] to [8]) and combination of both data sources were seldom explored with the exception of urban impervious surfaces [10]. While multispectral images enable to assess some topsoil properties such as organic carbon content [3] [11]&[12], they only indirectly deliver information on soil surface roughness. Now the mapping of soil surface roughness could be useful for the spatial assessment of agricultural systems through soil management practices. As a matter of fact, although topsoil roughness may be influenced by soil types through particles and aggregates sizes and shapes, it is likely to be even more strongly related to soil tillage operations and the developing of ridge and furrow patterns. This study aimed at assessing the potential of combining synchronous SPOT4 and ENVISAT/ASAR images for mapping tillage practices of bare agricultural fields over a 220 km²- peri-urban area located in the western suburbs of Paris (France). The approach relied on topsoil roughness measurements combined to the description of tillage operations: reference zones relying on both soil map information, the visual interpretation of the SPOT4 infrared coloured image and their standard of surface height at 28 sites were related to the backscattering coefficient of the ASAR image, then used for training/validating artificial neural networks (ANN) with 15 bootstrapping iterations.

2. MATERIALS AND METHODS

2.1. Study area

The study zone is the Versailles plain and the Alluets plateau area (48°46'-48°56' N; 1°50'-2°07' E, WGS, 1984) extending over 22 145 ha in the western Paris suburbs (Fig. 1). Located about 30 km West from Paris, this small agricultural peri-urban region has slender topographic contrasts, and controlled urban spread because its main NW-SE axis is in the view of the Versailles castle and dedicated to crop cultivation. Quaternary loess deposits and Holocene loessic colluvium leave a mark on all landforms, particularly plateaus where they have transformed into hortic or glossic luvisols according to the FAO classification [11], while calcaric, rendzic cambisols develop on plateau flanks, from limestones or calcareous colluvium. In addition to contrasted soils, agricultural system are devoted to cereal cropping. The main crop successions are composed of rapeseed/winter wheat/spring barley and sometimes corn or lucern, and managed with conventional tillage practices: late fall ploughing, followed by chisel and seedbed preparation for spring cereals.

2.2. Satellite imagery

A SPOT4/ASAR image pair was acquired over the study area on 16 March 2012 under perfectly clear sky conditions. The SPOT4 image had a near-nadir viewing and was orthorectified by Spot Image® as a Level 3 SPOTview® orthoimage with nearest neighbor resampling. The ASAR image (C band) had a high 41° incidence angle which is likely to better extract surface roughness [7]. It was georeferenced using the SPOT4 image as reference.

2.3. Field observations

A total of 78 squared sites with 2.70 m-size were observed over bare agricultural soils between 11 March and 6 April 2012. Field reflectance spectra were recorded at each site in the 350-1000 nm region with the FieldSpec® 3 portable spectroradiometer (Analytical Spectral Devices Inc., Boulder Co) then simulated into SPOT spectral bands [12]. The geographical position of each sub-square was recorded with a Trimble Pathfinder® DGPS with a 50 cm-precision. Soil roughness was estimated from the processing of stereoscopic photographs at each of the 2012 sites [13]. Soil samples were collected between 0 and 8 cm depth and soil moisture was determined gravimetrically at each site. Qualitative information about soil surface condition (crusted or not, ploughed, recently harrowed or rolled, presence/absence of sparse vegetation), the presence of coarse fragments, crop debris or organic manure, crop rotations and ploughing depth and frequency, was also collected. All field observations and measurements were made within ± 2 h of the solar noon.

2.4. Mapping approach with ANN

2.4.1. Delineation of training/validating areas

In order for training ANN then validating classified images, the infrared-coloured SPOT4 image was visually interpreted in order to delineate homogeneous zones based on both soil polygons and radiometric properties around each field site. These homogeneous areas were defined within a given agricultural field, that is to say were aimed at accounting for intrafield soil variability in combination with tillage operations.

2.4.2.Relationship between soil roughness and other topsoil properties

Although relationships between soil roughness characterized through the standard deviation of root mean square height (HRMS) and other topsoil properties such as reflectance and organic carbon content were investigated, they will not be detailed here. The relationships were studied between HRMS and the mean dB backscattering coefficient choosing a limited set of reference zones amongst the 78 sites. The criteria for reducing the dataset were the following: i) observations close to the imaging date between -6 days/+7 days with no rainfall event; ii) no field work and/or limited vegetation growth between field observation and imaging date. From the dB-HRMS curve, threshold values for HRMS were inferred. Reference zones were assigned to bare soil roughness classes according to these thresholds. Other reference zones were defined according to the topographical 1/25000 map of the French National Geographic Institute and/or based on field knowledge: forests, crops and grasslands, urban areas, water bodies.

2.4.3.Constructing ANNs and performance assessment

We used the 'Neural Net' layered feed-forward neural network classification implemented in ENVI v4.8. Each ANN was computed on the coregistered SPOT4 and ASAR images at 20 m resolution (i.e a total of 6 bands: the 4 SPOT bands and the HH and HV bands) specifying one hidden layers and 2000 iterations. We performed 15 bootstrap selections of training/validating sets amongst the chosen set of reference zones, and therefore obtained 15 classified images. These 15 classified images were stacked into a "hyperclassified image" and at each pixel, the spectra of the final assigned classes were calculated using the Hyperstat procedure developed by [16]. The final map was that of the first mode class, while the map of the first mode assignment frequency revealed classification uncertainty. The mean producer's, user's validation accuracy were computed from the 15 confusion matrices between validation zones and their corresponding pixels on classified images.

3. RESULTS & DISCUSSION

According to the selection criteria defined for reference zones for tillage practices, only 28 out of 78 reference zones were chosen (Figure 1). They were composed of 44 pixels in average (median: 41, min: 9, max: 99) i.e covered 1.76 ha.

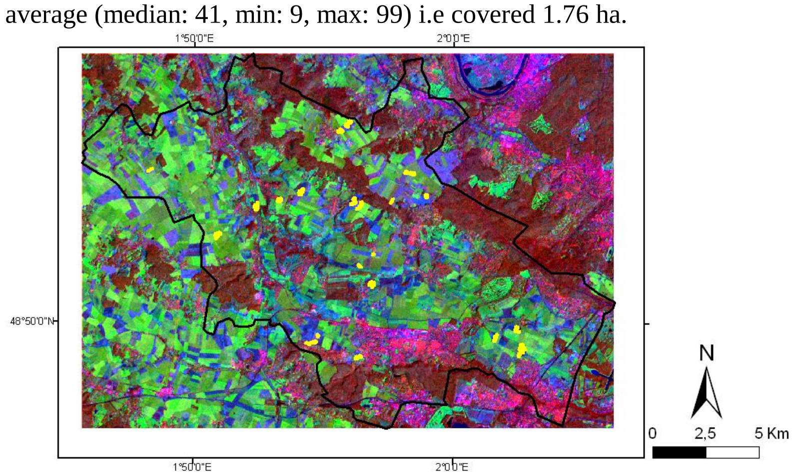

Figure 1. Colour-composite SPOT/ASAR image (red, HH band; green, near infrared b3 band; blue, green b1 band) over the study zone (black boundary) and locations of reference zones for tillage practices (yellow zones)

3.1. Sensitivity of radar signal to surface roughness

Following former results on the effect of incidence angles [7], the HH polarization (Figure 2) appeared to be better related to soil roughness compared to the HV one (not shown).

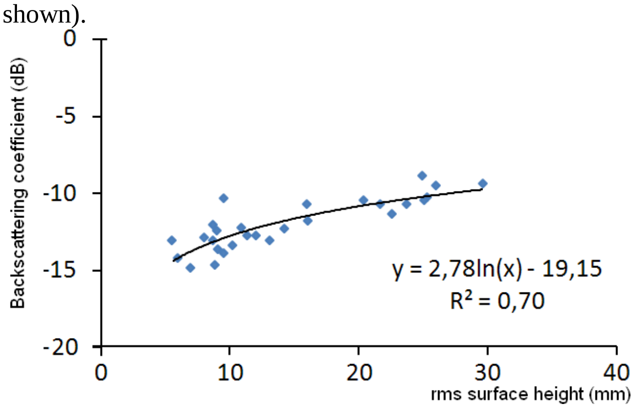

Figure 2. Dependance of radar signal in C-band (~5.6 GHz) with the surface roughness in HH polarization

As previously observed by [7] for similar soils, it is difficult to discriminate between roughnesses greater than around 15 mm. We therefore choose to map soil roughness according to two classes only: smooth and moderately rough surfaces (HRMS<15 mm) and rough surfaces (HRMS>15 mm). This 15 mm-threshold discriminates between soils freshly harrowed or in seedbed conditions (smooth surfaces) and soils still showing patterns of late winter plough (rough surfaces).

3.2. Map of tillage practices and land use - validation

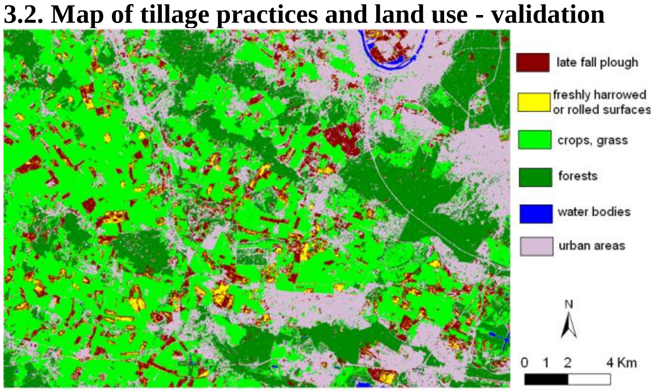

Figure 3. Final map of tillage practices (1rst mode)

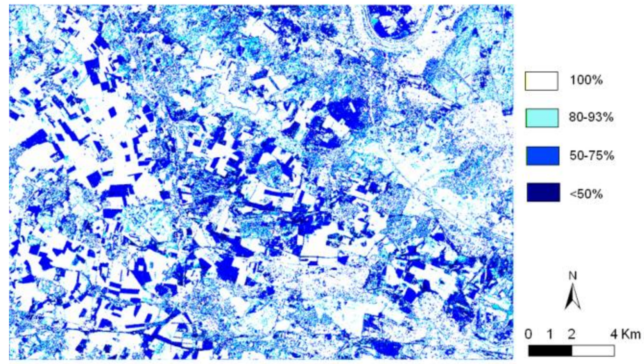

Figure 4. Map of assignment frequency

The final map of tillage practices and that of assignment frequency are shown in Figures 3 and 4.

The overall mean validation accuracy was 94.9%, while the producer's and user's mean validation accuracies were 91.6-81.5% and 61.8-75.4% for smooth and rough surfaces respectively. Even if these accuracies are encouraging, rough surfaces are less accurately mapped than smooth ones. However, less than 5.5% of the image pixels had an assignment frequency lower than 50%. Most bare soils had a higher assignment frequency comprised 50 and 75% while it was even higher for forests and urban areas.

4. CONCLUSION

These results show promises for further monitoring of tillage operations within a crop production campaign, in the perspective of the Sentinel-2 time series, but the recovering of contact with ASAR sensor which has been lost since last May 2012 is needed. Such knowledge of agricultural practices at consecutive dates is likely to facilitate the mapping of agricultural systems which otherwise proceed from time-consuming surveys to farmers.

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